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Research article

Remote sensing based deforestation analysis in Mahanadi and Brahmaputra river basin in India since 1985

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ABSTRACT

Land use and land cover (LULC) change has been recognized as a key driver of global climate change by influencing land surface processes. Being in constant change, river basins are always subjected to LULC changes, especially decline in forest cover to give way for agricultural expansion, urbanization, industrialization etc. We used on-screen digital interpretation technique to derive LULC maps from Landsat images at three decadal intervals *i.e.*, 1985, 1995 and 2005 of two major river basins of India. Rain-fed, Mahanadi river basin (MRB) attributed to 55% agricultural area wherein glacier-fed, Brahmaputra river basin (BRB) had only 16% area under agricultural land. Though conversion of forest land for agricultural activities was the major LULC changes in both the basins, the rate was higher for BRB than MRB. While water body increased in MRB could be primarily attributed to creation of reservoirs and aquaculture farms; snow and ice melting attributed to creation of more water bodies in BRB. Scrub land acted as an intermediate class for forest conversion to barren land in BRB, while direct conversion of scrub land to waste land and crop land was seen in MRB. While habitation contributed primarily to LULC changes in BRB, the proximity zones around habitat and other socio-economic drivers contributed to LULC change in MRB. Comparing the predicted result with actual LULC of 2005, we obtained >97% modelling accuracy; therefore it is expected that the Dyna-CLUE model has very well predicted the LULC for the year 2025. The predicted LULC of 2025 and corresponding LULC changes in these two basins acting as early warning, and with the past 2-decadal change analysis this study is believed to help the land use planners for improved regional planning to create balanced ecosystem, especially in a changing climate.

1. Introduction

The role of river basins as repositories of natural, environmental and cultural resources along with capturing, channelling, regulating and storing the fresh water for anthropogenic uses, makes them multifunctional units in all perspectives *i.e.*, hydrological, biophysical, socio-economic etc. (Dawei and Jingsheng, 2001; Wagner et al., 2002). Being in a constant process of changes, river basins are always subjected to the forces carried out in ecological, economic, social and cultural aspects i.e., the so called 'driving forces' of land use and land cover (LULC) change (Verburg et al., 2006). LULC change has been recognized as a key driver of regional and global climate change by influencing land surface processes whose subsequent impact on water cycle; energy balance and carbon cycle are realized and thus has an important implication for various policies prescriptions at national and international level

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(Wang and Zhang, 2001; Lambin et al., 2003). Cumulatively the LULC change, climate change and soil deterioration alters the hydrological cycle, and that progressively degrades ecosystem, decreases the quality of land resources, biodiversity and future of agricultural productivity (Das et al., 2017; Bajocco et al., 2012; Butchart et al., 2010; Dadhwal et al., 2010; Mishra, 2008).

LULC is interlinked with environmental and socio-economic systems. The driver plays leading role in LULC changes, and are derived from the interrelationship of the various elements such as altitude, slope, aspect, soil type, precipitation etc. are grouped as environmental; and population, literacy rate, household, drinking water facility, medical facility, etc. as socioeconomic (Briassoulis, 2000). Boserup (2002) showed the positive and negative impact of population on LULC as growing population might cause land degradation in short term but can enhance innovation and intensified agriculture by adopting conservation. The initiation of India's 'Green Revolution' to support a large population in terms of food security and sustainable economic development has led to expansion of agricultural area through widespread deforestation (Singh, 2000). Additionally, the rapid urbanization with the start of industrial revolution and globalization way back in 1970s has led to the encroachment of grasslands, wetlands, forests etc. (Fazal, 2001). Roy et al. (2015a) studied the decadal LULC changes in India during 1985, 1995 and 2005, and highlighted the loss of forest cover in central and northeast India, increase of cropland area in western India, growth of peri-urban area, and relative increase in plantations. Road accessibility, population proximity and temperature rise were found to be three major drivers of forest cover change in Hindu Kush Himalayan region (Murthy et al., 2016).

Brahmaputra (BRB) and Mahanadi (MRB), the two major River basins of India, hold huge population and have undergone severe deforestation during last decades mainly due to dam constructions, industrialization, urbanization and agricultural expansion in MRB; and shifting cultivation, urbanization and river shifting in BRB (Roy and Giriraj, 2008; Reddy et al., 2009). The Brahmaputra river is characterized by its large flow, enormous sediment load as erosion deposition problem, leading to continuous changes in channel morphology and river course change. The interaction of anthropogenic and natural system within two river basins is extremely contrast, yet deforestation is their major means of land cover change; thus, motivated to study and evaluate the land use fates deforestation meets in the two river basins in a comparison mode.

The spatial arrangement of LULC can be identified and mapped by aerial view of landscape or through remotely sensed satellite images (Roy and Behera, 2003). Remote sensing with its synoptic view, fast data acquisition and digital format suitable for computer processing, is one of the most successful and reliable data source in last few decades in recording spatio-temporal LULC change (Behera and Kushwaha, 2002; Lambin et al., 2003). Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data programme of NASA earth observation have been broadly employed in LULC studies providing a nearly continuous record of global land cover since 1972 focusing mainly in forest and agricultural areas (Campbell, 2007; Cohen and Goward, 2004).

Modelling of potential future LULC assigning a set of defined conditions offers the opportunities to examine the probable spatiotemporal changes at landscape level (Verburg et al., 2008; Behera et al., 2012). These models incorporate human decision making and environmental management policies while taking into account the processes that drive LULC change (Parker et al., 2003; Tang et al., 2009). Various modelling approach has been adopted to study the LULC changes (Lambin et al., 2000; Agarwal et al., 2002; Singh et al., 2015). Behera et al. (2012) have used CA-Markov model for future prediction of LULC scenario in part of the Mahanadi river basin, where they observed a significant gain in built-up and agriculture land at the cost of deforestation. The Conversion of Land Use and its Effects (CLUE) is a spatially explicit, LULC change model simulates based on an empirical analysis of location based suitability, preference and feature interactions at spatio-temporal dimension. The different versions of the CLUE model (CLUE, CLUE-s, Dyna-CLUE and CLUE-Scanner) are among the most frequently used LULC models. Limited studies have been carried out on LULC dynamics using the CLUE models in India, especially in MRB and BRB.

We have attempted to map the LULC status of the two river basins as Brahmaputra river basin (BRB) and Mahanadi river basin (MRB) using a pre-defined classification scheme from satellite data for the period of 1985, 1995 and 2005, following visual image interpretation technique. Further, we analysed the decadal LULC changes in these two along with the associated drivers of the corresponding years. We utilised a conversion model Dynamic Conversion of Land Use and its Effects (Dyna-CLUE) to predict the 2005 LULC map using 1985 (T1) and 1995 (T2) LULC maps at decadal scale with the corresponding drivers. This predicted 2005 LULC map was matched with the satellite-derived original 2005 map. Finally we used the drivers and satellite-derived LULC maps of 1985 (T1) and 2005 (T2) to predict the LULC map for the year 2025 at 20 years interval.

2. Study area

2.1. Mahanadi river basin

The study area MRB, one of the major river basins of India, situated on the eastern coast of the Bay of Bengal. Subarnarekha, Brahmani and Baitarni River basins were considered together under 'Mahanadi River basin' for the study (Fig. S1). These are rain-fed river basins accommodate thick population, mostly covered by agricultural land and forest. The basin covers mostly plains with an elevation range of 1–1500 m. Mahanadi river starts from in central Indian plateau of Chhattisgarh, flows eastwards through Odisha state before it culminates in Bay of Bengal, with total length of about 851 km. It lies between 16.8° N and 23.5° N latitude and 80.2° E–88° E longitudes within elevation range of 196 m and 877 m. Many dams, irrigation networks and barrages are present in the basin, the most prominent of which is the Hirakud Dam, the largest reservoir in Asia with 746 km^2 catchment area. During its traverse, a number of tributaries join the river on both the flanks with 14 major tributaries, of which 12 join it upstream of Hirakud reservoir and 2 in the downstream of it. The climate is tropical monsoon with a south west monsoon during June and July. The annual rainfall is 1360 mm of which 86% (1170 mm) is contributed from the monsoon season. The temperature ranges from a minimum of 4 °C–12 °C in winters to a maximum of 42 °C–45.5 °C in May. The main soil types are red and yellow soil, mixed red and black soils.

2.2. Brahmaputra river basin

BRB is both glacier and rain fed basin, dominated with forest cover and support relatively low population density. BRB covers mostly the mountainous region with an elevation range of up to 8437 m. The Brahmaputra river originates from Himalayan Kailash ranges and its basin spreads over four countries including China, Bhutan, India and Bangladesh having a total area of nearly 5, 80,000 km^2. The Indian area covered by this basin is nearly 6% of the country's total geographic area, has been considered for study. It extends from 21.5̊N-29.5̊N latitude and 88̊E–98̊E longitude, occupying nearly 280288 km^2 (Fig. S1). The upper basin lying in the Arunachal Pradesh and Nagaland states of India is mostly

mountainous with narrow valleys where the river has a high gradient of 16.8 m km^{-1}. The climate of the basin follows the normal Indian pattern of four seasons as winter, summer, monsoon and autumn. The weather is generally changed by the passage of western disturbances across the region with relatively less rainfall occurring in January and February along the hills. Overall, 66–85% of the annual rainfall is contributed from the monsoon season and 20–30% contributions from pre-monsoon season (Sarma, 2005). The mean temperature in the basin ranges from mean minimum of 15 °C–17 °C during January, to a mean maximum of 27.5 °C–30.0 °C in July. The dominant soil type of the River basin is red loamy and alluvial soil.

3. Methodology

The analysis was divided into three segments (i) LULC mapping and change detection, (ii) Analysis of drivers (iii) LULC modelling. Multi-temporal satellite data *i.e*., Landsat MSS (multispectral scanner) images for 1985 and 1995, and TM (Thematic Mapper) data for 2005 were downloaded from United States Geological Survey (USGS) portal (Table S1). Radiometric correction using image enhancement techniques followed by geometric correction were applied on the satellite data. All the data were transformed to Universal Transverse Mercator (UTM) projection with WGS84 datum. The mapping was done on 1:50,000 scale following two level classification scheme of International Geosphere and Biosphere Programme (IGBP) hierarchical classification system. Primarily, the LULC vector map of 2005 was prepared with on screen digitization using visual interpretation of satellite images. The vector LULC of 2005 was overlaid on the 1995 satellite data (Landsat TM) and the polygons were modified where the changes had taken place to prepare the LULC of 1995. Same procedure was repeated for the preparation of 1985 LULC map by overlaying the vector LULC map of 1995 on 1985 satellite data (Landsat MSS as provided by USGS: http://glovis.usgs.gov). This protocol takes care of different spatial resolution satellite data use (Roy et al., 2015a,b). Information gathered from ground truthing, literature survey and other supplementary sources were also utilised during interpretation. Accuracy assessment was also done by taking randomly stratified points for each class to assess the quality of the information derived. We used 200 points with random distribution over each class for evaluating classification accuracy of the LULC maps. The ArcGIS 9.3 software was used for polygon editing; whereas interpretation and accuracy assessment was done in ERDAS IMAGINE 9.2 software. The maps were further crossed to derive the changes in LULC patterns using *post-classification change detection* approach. This allowed us to quantify the changes of a particular LULC to another LULC category by producing a change matrix.

3.1. Driver dataset

The driver datasets fall into two categories *i.e*., environmental and socio-economic drivers that were further classified as primary and secondary data (Table S1). All the primary driver datasets were procured and projected to same coordinate system of UTM with WGS84 datum.

3.1.1. Environmental drivers

Shuttle Radar Topographic Mission (SRTM) derived elevation data available for the period of 2000 was used for all three time periods owing to its relatively static nature. Slope and aspect were calculated from elevation data, whereas the soil map on 1:1 million scale made by the National Bureau of Soil Survey and Land Use Planning (NBSS-LUP) was used directly. The total rainfall was calculated by adding the daily rainfall of a year, while the annual mean temperature was calculated by averaging; for 1985, 1995 and 2005 respectively (Table S1).

3.1.2. Socio-economical drivers

All socio-economic driver data was collected at district level were added as attribute table into district vector file (Table S1). The water body, deciduous and evergreen broad leaf forests were masked out from the district vector file, considering these areas were not holding socio-economic data. Population density was calculated by division with respective district area in masked file. Thereafter the masked out features were added into the district vector file and converted into raster format.

A fishnet of 250 × 250 m^2 was created within the study area, in which all the environmental and socio-economic data was appended. The majority classes falling in a grid were considered for the grid value. This method was incorporated to standardize the spatial domain overcomes the pixel shifts among various data. Again this method was adopted because at course resolution the models captures the relation between the land covers with the drivers, where the aggregate impact of different factors and processes act below resolution unable to capture (Verburg and Chen, 2000; Walsh et al., 1999). Finally, the grided data was converted to raster and normalized to a scale of '0 to 1' for uniformity.

3.1.3. Analysis of LULC change with driver dynamics

To assess the impact of drivers on LULC change, the major conversions changed >100 km^2 was chosen. As representative of each category, we selected >300 random points from each LULC change category and >200 random points where no-change took place. The corresponding changes in drivers were calculated using simple subtraction method. This change in driver data was extracted for each representative point. A binary logistic regression analysis was performed on the representative points to estimate the statistical parameters *i.e*., β-coefficient and significance level in Statistical Packages for the Social Sciences (SPSS) software.

3.2. Prediction of LULC change

For LULC modelling, the freely available Dyna-CLUE (Dynamic Conversion of Land Use and its effects) model [CLUE version 2.0] was used (Verburg and Overmars, 2009). This model works depending on two basic distinct modules as spatial and non-spatial; where the spatial module takes inputs as initial year LULC map (starting year of simulation), restriction polices as study region map (restricted, unrestricted and no-data area) and drivers that cause LULC change; and the non-spatial module takes inputs as land use requirements (LULC area statistics of all the years of simulation: demand file), locational characteristics as relationship of LULC with the drivers (for land use specific locational suitability), land use type specific conversion settings as conversion matrix (the type of land conversions that are allowed and not) and conversion elasticity (how easy a land cover converts to other), and the convergence criterion (to restrict the model over and under prediction). The above-mentioned parameters create a set of conditions and possibilities, based on which the model uses an iterative procedure to find the probability of occupancy of each LULC class in a pixel and substituted with the class having highest probability.

The demand of each land covers of the year 1985, 1995 and 2005 were obtained from the LULC maps and for the intermediate years, interpolation and extrapolation techniques were applied.

The relation between the land cover and drivers were expressed through β-coefficients, calculated using SPSS statistical tool using binary logistic regression with forward conditional method and 20 iterations.

The binary logistic regression can be mathematically expressed

as:

$$P(Y) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n}}$$

where, P is probability of Y occurring, i.e., presence or absence of a particular land cover class, e is natural logarithm base, β_0 is interception at y-axis, β_1, β_2, …, β_n are line gradients or the regression coefficient corresponds to the variables X_1, X_2, …, X_n (www.let.rug.nl/nerbonne/teach/rema-stats-meth-seminar/presentations/Binary-Logistic-Regression-Schueppert-2009.pdf).

Positive and negative β-coefficients associated with each driver signify positive and negative correlations with corresponding driver respectively. Positive Exp (B) indicates increase in the probability as the value of driver increases and vice-versa.

The values in land use specific conversion matrix was defined in form of 1 or 0 for possible and impossible conversions; for example, cropland can be converted into built-up but the reverse is not possible, hence in conversion matrix it will be assigned 1 and 0 for the above two respective conversions.

In case of conversion elasticity, according to the model set up, lower the value, easier to be converted to the other classes and vice-versa; *e.g.*, if conversion elasticity of cropland and forest were 0.3 and 0.6, to fulfill a demand, cropland would be converted more easily than forest.

Convergence criterion takes the inputs as the allowed errors in the average and maximum deviation between the demanded and predicted area. More detailed information about these inputs and model functionality are available minutely in the user's manual (Verburg and Overmars, 2009).

With the decadal LULC maps and drivers (1985 and 1995 at 10 years interval), the LULC of 2005 was predicted and model performance was evaluated and validated by comparing the visually interpreted LULC of 2005. Since the map and driver data for 2015 was not available at the time we had to follow a trend of 10 years to assess the efficacy of model. Once we were confident about the results at 10 years trend (validation accuracy > 90%) we followed the same methodology for 20 years trend i.e. 1985 to 2005 to predict the LULC map of 2025. The area accuracy was computed by comparing the predicted area with the observed area and the spatial accuracy was computed incorporating each pixel of these two data through the User's, Producer's, Overall accuracy and *Kappa* value. After achieving satisfactory results, the model projection was continued with LULC maps and drivers of 1985 and 2005 to predict the LULC of 2025 at an interval of 20 years.

4. Results

4.1. Decadal (1985-1995-2005) LULC mapping

LULC maps with 13 classes were prepared for the years 1985, 1995 and 2005 using on-screen visual interpretation technique (Table 1; Fig. 1a–c).

Cropland with nearly 55% area was the dominant land use in MRB in all three decadal years i.e., 148147 km^2, 148861 km^2 and 148892 km^2 for 1985, 1995 and 2005 respectively, whereas salt pans occupied least area (Table 1; Fig. 1). Among forest classes deciduous broad leaved forest occupied maximum area with 70408 km^2, 69638 km^2, and 69382 km^2 in 1985, 1995 and 2005 respectively. Mixed forest occupied nearly 4% of the total geographic area showing 11233 km^2, 10948 km^2, 10908 km^2; whereas scrubland occupied around 5% of the total area covering 15191 km^2, 14925 km^2 and 14840 km^2 areas in 1985, 1995 and 2005 respectively. Very small fraction (percentage of the total area) of areas was covered by mangrove, barrenland and aquaculture (Table 1; Fig. 2a–c).

In BRB, evergreen broad leaved forest occupied maximum area with 105014 km^2, 104508 km^2 and 103787 km^2 contributing to nearly 37% of total geographic area in 1985, 1995 and 2005 respectively (Table 1; Fig. 2a–b). Mixed forest class was observed as the second largest land cover contributing to nearly 22% (63285 km^2, 62587 km^2, and 61812 km^2 in 1985, 1995 and 2005 respectively). Cropland contributed to nearly 16% land use with 46525 km^2, 48028 km^2 and 49242 km^2 areas in 1985, 1995 and 2005 respectively. Deciduous broad leaved forest, occupied nearly 3.4% area with 9529 km^2, 9387 km^2, 9074 km^2 and, snow and ice 9737 km^2, 9765 km^2, 9665 km^2 respectively. Very less area was occupied by fallow and wasteland. Water body showed a spread of nearly 4.5% area with 12565 km^2, 12527 km^2 and 12731 km^2 in 1985, 1995 and 2005 respectively (Table 1; Fig. 2a–b).

To estimate the classification accuracy, error matrices were generated by comparing the LULC with randomly stratified points and high resolution *Google Earth* imagery for each class; have shown >89% overall classification accuracy and >0.87 *kappa* accuracy (Tables S2a and S2b). This is beyond the minimum acceptable level of accuracy (85%) for any further utility according to USGS. Many classes showed up to absolute levels of producer's and user's accuracy with the majority of them with >90% for both the basins (Table S2). Lower producer's accuracy was observed for fallow land (67%) in 1985, salt pan (50%) in 1995 in MRB; and wasteland (64%) in 1985 in BRB.

4.2. Decadal land use and land cover change (LULC change)

We observed an overall decrease in forest classes during past 3 decades and an increase in built up, cropland classes in both the river basins (Figs. 2a and 3a,b; Table 2a; Table S3) [few changes are shown using satellite images (Figs. S2, S3 & S5)]. In MRB, among forest classes the maximum decrease was observed in the deciduous broad leaved forest (1026 km^2) followed by mixed forest class (325 km^2) during 1985–2005, of which the major decrease was during 1985–1995 *i.e.*, 770 km^2 and 285 km^2 respectively (Tables 2a and S3a). Loss of 351 km^2 and 85 km^{2}area in shrub land and barren land respectively was observed from 1985 to 2005. 745 km^2 and 569 km^2 areas were increased in cropland and built-up class during 1985–2005, of which 714 km^2 and 340 km^2 increases were observed during 1985–1995 for cropland and built-up respectively. Most of the cropland expansions were converted from forest, fallow land, scrubland, water body and waste lands; whereas the croplands were mostly converted into built-up areas in its surroundings (Figs. 2a and 3a, b; Table 2a). An addition of 360 km^2 area was observed in water body from 1985 to 2005, whereas >100% (127 km^2) expansion in the aquaculture area was noticed during 1995–2005 compared to 1985 to 2005 mostly at the cost of crop lands (Table 2a).

In BRB, the mixed forest suffered maximum loss with 1473 km^2 and 700 km^2, followed by evergreen broad leaved forest with 1227 km^2 and 775 km^2 during 1985–1995 and 1995 to 2005 respectively (Figs. 2b and 3c,d; Table 2b; Table S3b) [few changes are shown using satellite images (Figs. S2, S3 & S5)]. In comparison, deciduous broad leaved forest observed less deforestation around 455 km^2 during 1985–2005 and 313 km^2 during 1995–2005. On the other hand, maximum increase was observed in cropland with 2717 km^2 followed by built-up with 231 km^2 during 1985–2005. In contrast to MRB, built-up areas were mostly increased at the cost of mixed forest; however the cropland areas shows similar type of conversion as MRB, where forest classes with fallow land, grass land, scrub land, water body and waste land were converted to croplands. Most of croplands expansion from water body class were observed within the flood plain of Brahmaputra river (Figs. 2b and

Table 1
Area (in km^2) estimates of various LULC classes for Mahanadi (MRB) and Brahmaputra (BRB) river basins.

LULC Class	MRB				BRB			
	1985	1995	2005	2025	1985	1995	2005	2025
Aquaculture (AQ)[a]	72.19	81.75	198.5	331.69	–	–	–	–
Barren land (BL)	754.63	718.19	670.13	588.81	2112.25	2090.31	2150.56	2187.69
Built-up (BU)	3408.69	3749.44	3977.94	4549.69	3415.63	3523	3647.38	3886.38
Cropland (CL)	148147	148861	148892	149701	46524.9	48027.8	49242.1	51916.5
Deciduous broad leaved forest (DBF)	70408.3	69637.7	69382.4	68339.3	9529.25	9386.44	9074.25	8597.94
Evergreen broad leaved forest (EBF)[b]	–	–	–	–	105014	104508	103787	102500
Fallow land (FL)	5204.69	5059.13	5065.81	4922.75	151.5	149.13	156.06	166
Grass land (GL)[b]	–	–	–	–	8808.44	8632.44	8692.38	8577.69
Mixed forest (MF)	11233.2	10947.6	10908.3	10574.7	63285.4	62586.9	61812.4	60279.3
Mangrove (MG) [a]	220.56	199.06	195.63	170.19	–	–	–	–
Plantation (PL)	3404.13	3420.31	3503.54	3599.81	8213.44	8179.56	8196.75	8189.19
Saltpan (SP) [a]	15191.4	14924.8	14839.8	14489.8	–	–	–	–
Scrub land (SL)	22	22.06	22.75	24.31	9736.5	9765.13	9665.44	9592.06
Snow & Ice (SI)[b]	–	–	–	–	10679.4	10649.8	10852.9	11010.3
Water body (WB)	7276.88	7607.75	7637.38	7974.25	12564.9	12527.3	12730.8	13078.6
Waste land (WL)	1132.06	1246.69	1181.81	1209.44	253.25	263.69	280.94	307.69

(Classes are available in MRB[a] and BRB[b] only).

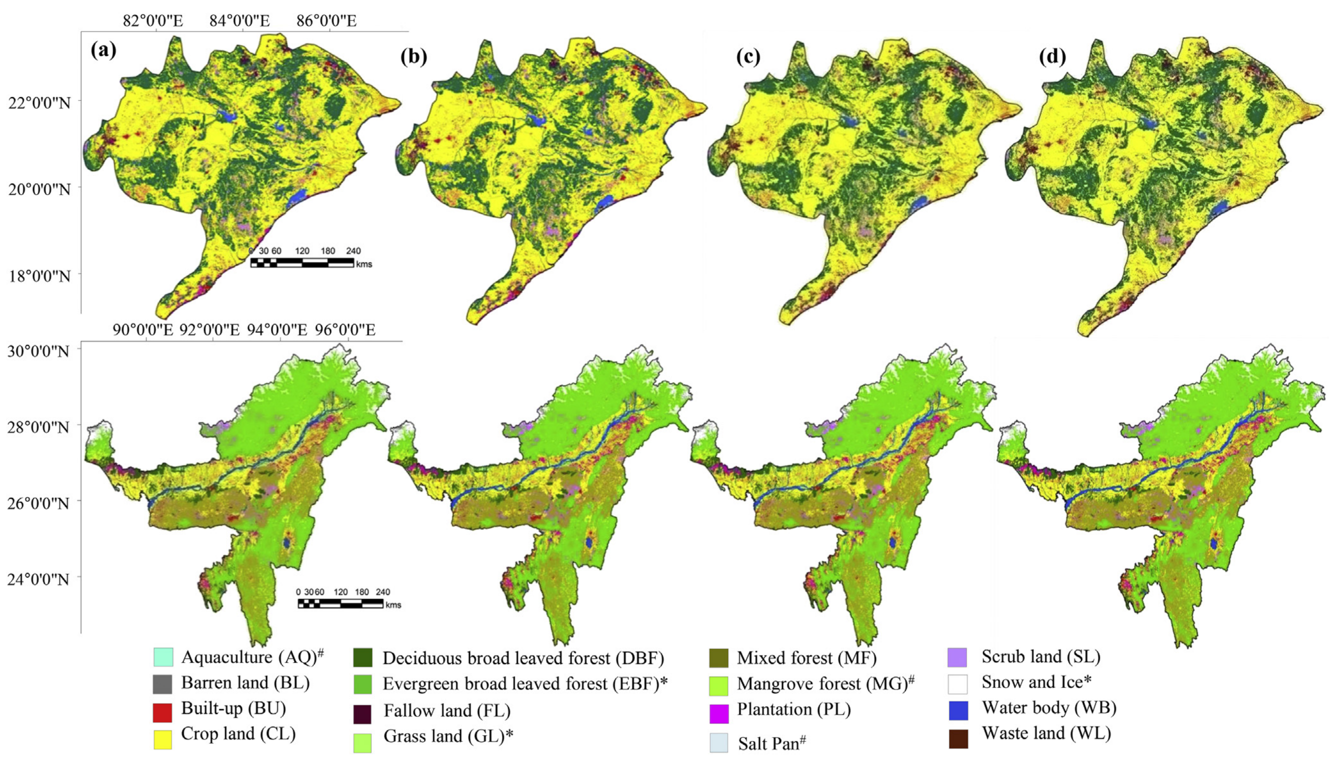

Fig. 1. Classified LULC map of MRB and BRB for the year (a) 1985 (b) 1995 (c) 2005; and (d) predicted- 2005 (Classes are available in BRB* and MRB# only).

3c,d; Table 2b; Table S3b). The interclass conversion of cropland and water body was mostly due to frequent shifts of course of Brahmaputra river.

4.2.1. Comparison of the modelled LULC map of 2005 with actual LULC map of 2005

To validate the modelling accuracy, the LULC of 2005 was predicted using the LULC maps and drivers of 1985 and 1995; and validated with the visually interpreted LULC map of 2005 (Fig. 1c and d). The predicted LULC map of 2005 showed a very close agreement with the reference map of 2005 (Tables S4a and b). We received 98% overall accuracy (kappa accuracy of 0.97) in MRB (Table S4a) and 97% overall accuracy (kappa accuracy of 0.96) in BRB (Table S4b). The class-wise accuracy varied with homogeneous classes (forest) having higher matching than heterogeneous classes (cropland and wasteland). With satisfied modeling accuracy, the LULC map for the year 2025 was predicted using the LULC maps of 1985 and 2005 with corresponding drivers keeping 20 years interval.

4.3. Analysis of drivers

All the socioeconomic drivers showed increasing trend which are directly proportional to the deforestation and cropland expansion (Fig. S4). Distance to built-up area, distance to forest and distance to water body demonstrated the role of proximity with

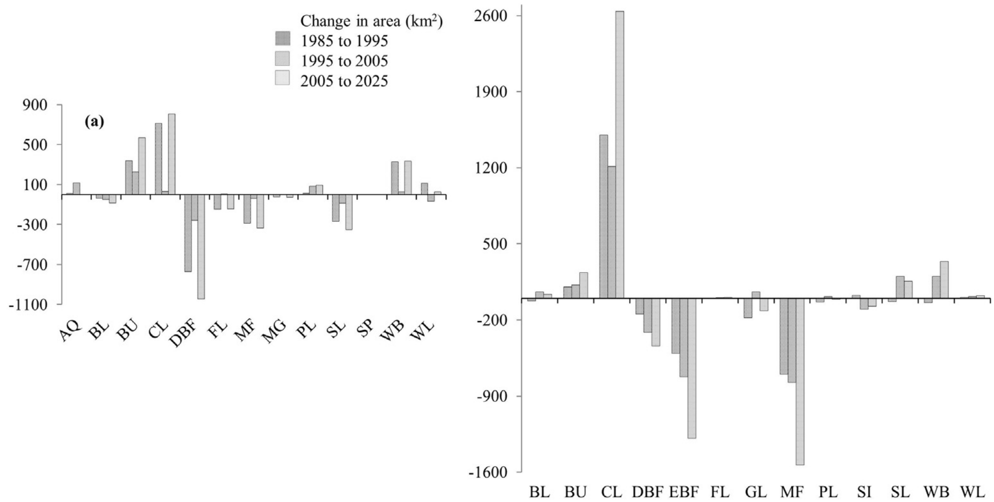

Fig. 2. Bar chart showing change in LULC area estimates during 1985–1995, 1995–2005 and 2005–2025 for (a) MRB and (b) BRB.

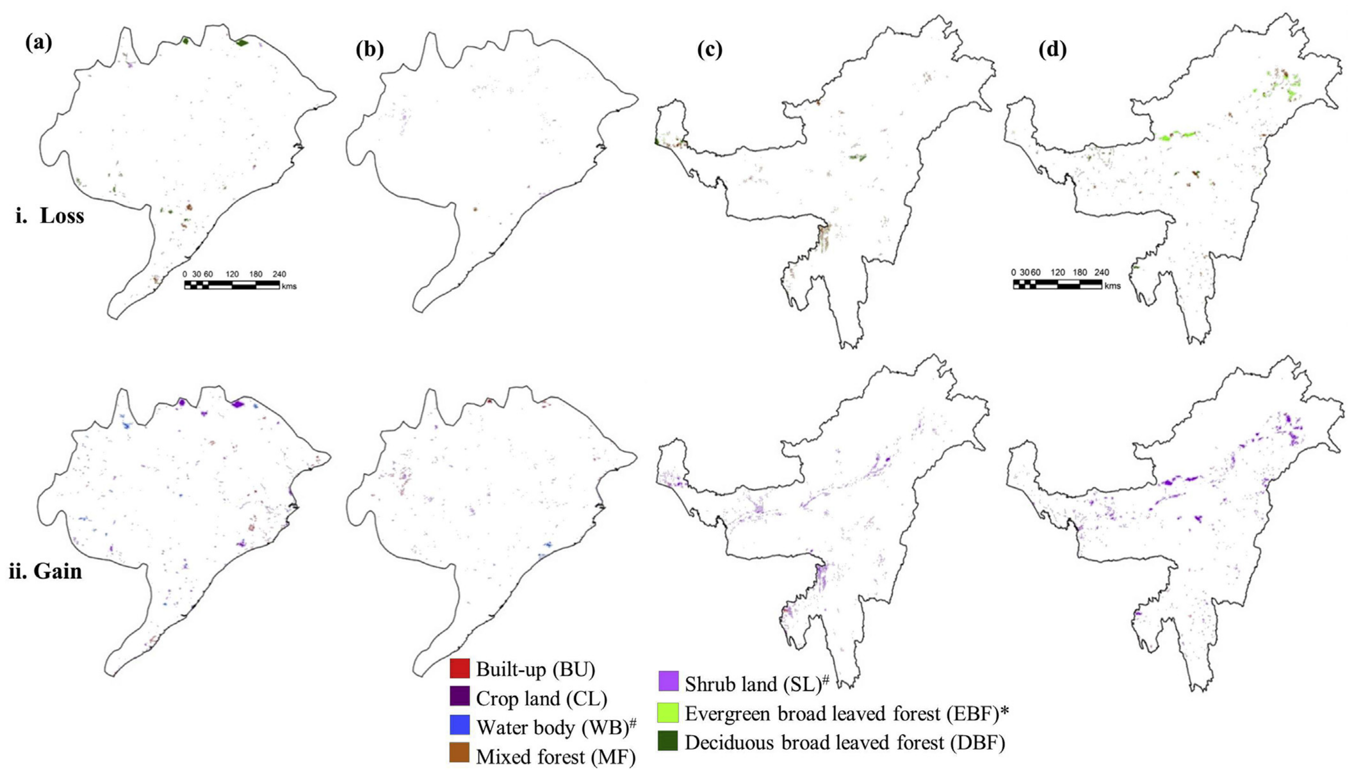

Fig. 3. (i) Loss and (ii) Gain maps for major classes of MRB during (a) 1985–2005, (b) 2005–2025 and BRB during (c) 1985–2005, (d) 2005–2025 (class is available in MRB# and BRB* only) Classes with >200 km^2 loss and gain area are only shown in maps.

decadal variation in LULC change.

In MRB, as expected the highest correlation was observed for deciduous broad leaved forest, mixed forest, mangrove and water body classes with distance drivers i.e., distance to built-up, distance to forest and distance to water body respectively, showing negative relationship (*i.e.*, −673.83, −313.58, −497.21, −735.55 and −317.8 respectively) (Table 3a). The deciduous broad leaved forest showed negative correlation with average temperature (β, −10.76). Mangrove demonstrated high negative correlation with total population (β, −493.15), and mixed forest showed positive correlation with sex ratio (β, 16.64) (Table 3a). Elevation and slope showed a negative influence on cropland with β values of −16.33 and −1.68 respectively, whereas sex ratio and establishment showed high correlation with cropland having β values of 8.25 and 5.1 respectively. Plantation showed a positive correlation with sex ratio and establishment having β values of 31.26 and 15.8 respectively followed by a negative correlation with working population and total population with β values of −14.03 and −11.19 respectively. Road length showed the least correlation with most of the classes (Table 3a).

In BRB, we observed high correlation of distance to forest for evergreen broad leaved forest and deciduous broad leaved forest

Table 2
Change area matrix of classified LULC for **a.** MRB and **b.** BRB during 1985–2005.

(a)		2005												
		AQ	BL	BU	CL	DBF	FL	MF	MG	PL	SL	SP	WB	WL
1985	AQ	60	0	0	9	0	0	0	0	1	0	0	0	2
	BL	0	586	2	34	1	15	0	0	21	19	0	3	75
	BU	0	0	3402	5	0	0	0	0	0	0	0	1	0
	CL	44	26	358	147050	0	0	0	0	26	0	0	563	80
	DBF	0	28	35	643	69285	53	78	0	54	81	0	128	24
	FL	0	0	16	243	0	4906	0	0	3	24	0	11	1
	MF	0	13	26	98	31	21	10780	0	55	113	0	73	26
	MG	5	0	1	4	0	0	1	181	2	0	0	14	14
	PL	1	0	39	12	0	10	0	1	3212	68	0	18	44
	SL	4	19	65	268	62	50	46	0	77	14410	0	127	65
	SP	0	0	0	0	0	0	0	0	0	0	21	1	0
	WB	42	0	4	397	3	8	1	9	13	72	1	6672	56
	WL	43	0	31	129	1	4	2	6	40	52	0	28	797

(**b**)		2005												
		BL	BU	CL	DBF	EBF	FL	GL	MF	PL	SI	SL	WB	WL
1985	BL	2025	1	0	0	4	0	15	9	0	58	1	0	2025
	BU	0	3393	12	0	0	0	0	3	2	0	1	4	0
	CL	0	41	45594	0	0	24	8	0	49	0	3	800	0
	DBF	0	20	363	9044	2	0	15	3	11	0	15	55	0
	EBF	9	29	995	0	103708	4	43	11	13	6	56	136	9
	FL	0	0	26	0	0	121	0	0	0	0	0	4	0
	GL	9	2	197	3	23	0	7700	3	4	126	1	721	9
	MF	5	113	868	5	16	1	40	61755	40	0	194	243	5
	PL	0	27	99	2	0	0	1	3	8053	0	2	26	0
	SI	101	0	0	0	14	0	24	0	0	9475	122	1	101
	SL	1	17	184	1	4	0	3	5	0	0	10432	29	1
	WB	0	4	885	19	16	6	837	20	25	1	26	10636	0
	WL	0	0	18	0	1	0	6	1	0	0	1	76	151

Table 3a
Co-efficient generated from LULC map and driver interaction for MRB.

AQ	EL	SL	DW	SR	LR	EB	PD	DT	RF	SD	TP	DB	WP	DP	AS	MT	MF	RL
	−541.23	−121.74	−32.39	25.94	20.7	−20.46	−19.88	7.53	−5.49	−4.83	−3.53	3.01	2.83	2.4	2.21	1.14	0.55	−0
BL	SR	MT	TP	EB	RF	LR	WP	DP	PD	EL	RL	DB	DW	DT	SD	SL	MF	AS
	25.36	−15.68	−8.08	6.15	−5.87	5.48	−3.65	−1.88	1.57	1.29	−0.83	−0.72	0.61	0.51	−0.5	0.36	0.22	0.07
BU	DB	SR	TP	LR	MT	SL	EL	EB	AS	DT	RF	DP	WP	RL	DW	MF	PD	SD
	−673.83	3.38	−1.56	1.04	−0.88	0.87	−0.69	0.61	0.43	0.42	−0.39	−0.24	−0.23	0.21	−0.17	−0.2	0.07	−0
CL	SL	SR	EB	DP	WP	MT	DT	TP	EL	LR	PD	RF	SD	DB	MF	AS	RL	DW
	−16.33	8.25	5.1	3.94	−3.2	−3.14	1.82	−1.75	−1.68	−1.26	0.83	0.55	0.48	0.29	−0.19	−0.2	−0.2	0.14
DBF	DP	MT	DT	EB	SR	WP	SL	RF	TP	EL	DW	MF	RL	DB	AS	PD	SD	LR
	−313.58	−10.76	−5.43	−4.54	−4.13	2.98	2.7	2.41	1.56	1.29	1	0.65	−0.62	0.39	0.3	−0.2	−0.2	−0.1
FL	SR	EB	SL	MT	TP	WP	PD	EL	RF	DP	DW	DB	DT	LR	MF	AS	SD	RL
	20.02	−15.13	−10.98	−10.32	7.4	6.46	−5.27	2.98	−2.59	−2.46	−1.78	−1.42	1.28	0.83	−0.72	0.09	−0.1	0.03
MF	DP	SR	MT	EB	WP	DT	RF	SL	EL	TP	MF	SD	LR	AS	DW	PD	DB	RL
	−497.21	16.64	6.83	3.24	−2.74	2.66	−2.55	2.09	−0.92	−0.7	−0.51	0.44	0.39	−0.31	−0.21	0.11	−0.1	0.03
MG	DP	TP	LR	EB	EL	SR	WP	MF	MT	SL	DT	DW	DB	RF	RL	AS	SD	PD
	−735.55	−493.15	431.8	272.19	−244.4	163.44	−145.8	−107.8	−20.09	−13.8	12.89	−6.78	6.43	6.11	2.76	0.6	−0.6	−0.4
PL	SR	EB	WP	TP	MT	LR	RF	SL	EL	DT	DW	RL	DP	PD	AS	DB	SD	MF
	31.26	15.8	−14.03	−11.19	10.42	8.2	−6.97	−4.61	−4.42	3.06	2.51	1.19	−1.13	1.12	0.68	0.35	−0.3	−0
SP	SR	MT	DP	SL	WP	EB	PD	RL	EL	DT	LR	RF	DW	AS	TP	MF	DB	SD
	6.29	4.41	−3.82	3.29	−2.47	2.02	−1.86	1.05	0.97	0.92	0.9	0.47	0.42	0.19	0.16	−0.1	0.09	0.01
SL	MT	EL	SR	LR	EB	SL	RF	TP	WP	MF	DB	DT	PD	DP	SD	DW	RL	AS
	−1870.3	−1280.1	931.7	−300.4	234.46	−212.1	176.23	173.3	−134.8	−88.3	−47.2	32.1	21	−14.9	10.5	7.23	−3.4	2.17
WB	DW	SL	MT	EB	DT	TP	WP	EL	PD	LR	SR	AS	RF	MF	SD	DB	DP	RL
	−317.8	−20.11	−12.28	−7.84	−5.54	4.94	4.81	−4.67	−2.06	−1.79	−1.77	−1.48	1.29	0.69	−0.65	−0.5	−0.1	0
WL	EB	WP	MT	EL	SR	TP	RF	AS	SD	DT	LR	DB	DP	MF	DW	SL	PD	RL
	15.59	−14.2	−6.61	−6.52	4.81	−3.73	−3.44	−3.18	−2.07	1.62	1.5	−1.4	−1.1	−0.99	−0.94	−0.9	−0.6	0.55

with β values of −340.3 and −247.17 respectively, (Table 3b). Mixed forest showed a negative correlation with elevation (β, −7.88) followed by a positive correlation with slope (β, 7.04; Table 3b). Cropland was negatively correlated with slope (β, −7.59) followed by a positive correlation with literacy rate. Built-up land showed positive correlation with average temperature and literacy rate with β values 4.3 and 3.39 respectively (Table 3b). Distance to water body and slope were the most influencing drivers showing negative correlation for water body with β values −278.4 and −8.27 respectively (Table 3b). Elevation was the most influential driver for snow and ice class with positive correlation with β value 32.36. Aspect has minimal values indicating least correlation with most of the drivers (Table 3b).

Table 3b
Co-efficient generated from LULC map and driver interaction for BRB.

BL	EL	MT	LR	RF	TP	DP	PD	EB	DB	SD	WP	MF	DW	DT	RL	AS	SL
	12.5	−7.43	7.09	6.53	−4.36	4.21	2.82	1.32	1.15	0.85	0.6	0.47	0.32	−0.27	0.15	0.02	0
BU	DB	MT	LR	SL	EL	EB	AS	PD	DP	WP	RL	RF	TP	DT	SD	MF	DW
	−805.89	4.3	3.39	−1.85	−0.95	0.85	0.67	0.49	0.34	0.29	0.29	−0.26	−0.25	0.22	0.1	−0.09	−0.08
CL	SL	LR	MT	EL	DW	DB	DP	DT	RF	PD	EB	MF	WP	RL	TP	SD	AS
	−7.59	5.06	−4.06	−2.71	−2.34	−1.37	1.28	1.17	−1.05	0.82	0.77	0.54	0.35	0.23	−0.17	−0.13	−0.04
DBF	DP	MT	EL	EB	WP	SL	MF	TP	PD	RL	DW	DB	SD	LR	RF	DT	AS
	−247.17	−29.68	−15.45	−3.13	−2.92	−2.79	−2.16	1.76	1.41	1.25	1.09	−0.94	0.65	−0.61	0.51	−0.14	−0.08
EBF	DP	MT	SL	LR	RL	PD	RF	DB	DW	MF	EB	EL	AS	WP	TP	SD	DT
	−340.3	19.45	5.29	−2.43	−2.28	1.37	−1.02	0.84	0.73	0.66	−0.51	0.47	0.45	0.3	−0.23	−0.19	−0.06
FL	SL	DB	EL	DW	MF	MT	EB	PD	LR	DT	SD	RF	RL	AS	TP	DP	WP
	−16.63	−12.12	6.72	−2.81	−2.81	−2.43	−1.75	1.73	1.54	1.38	1.09	1.06	0.82	0.74	−0.45	0.14	0.1
GL	EL	LR	PD	DB	RF	EB	DP	TP	SL	SD	MT	MF	DT	WP	DW	RL	AS
	5.41	5.32	−3.53	3.33	3.09	2.94	−2.89	1.85	−1.24	−0.9	−0.8	−0.71	−0.69	−0.59	−0.58	0.25	0.17
MF	EL	SL	LR	PD	MT	DW	DP	EB	SD	TP	DB	RF	AS	WP	DT	RL	MF
	−7.88	7.04	6.07	−5.67	3.96	1.69	1.42	1.35	0.91	0.9	−0.74	−0.24	−0.23	0.18	−0.1	−0.04	0
PL	MT	EL	LR	DB	SL	RL	PD	DW	WP	DT	DP	MF	EB	SD	RF	AS	TP
	20.37	−11.91	5.15	−5.1	−4.93	3.42	3.22	3.13	1.96	−1.82	−1.39	0.6	0.4	0.38	−0.34	−0.27	0.09
SI	EL	DP	TP	RF	PD	LR	MF	DT	DW	EB	MT	RL	WP	DB	SL	SD	AS
	32.36	−5.42	−5.21	4.38	4.37	−4.35	−4.17	−3.36	3.31	2.36	−1.87	1.78	−1.68	1.31	−0.56	0.48	0.02
SL	MT	EL	LR	RL	EB	DB	DW	MF	TP	PD	RF	DT	SD	AS	WP	SL	DP
	11.6	5.35	4.04	3.72	1.9	−1.88	−1.85	−1.69	−1.34	−1.11	−0.63	0.43	0.39	−0.37	0.35	0.32	0.27
WB	DW	SL	EL	LR	DP	TP	PD	MT	RL	DT	AS	DB	EB	WP	SD	RF	MF
	−278.4	−8.27	−3.17	−2.24	1.84	−1.79	1.79	1.61	0.53	−0.51	−0.4	−0.38	0.36	0.33	−0.31	−0.3	−0.09
WL	DW	SL	DP	LR	RF	TP	DB	PD	EB	MT	MF	EL	WP	DT	RL	SD	AS
	−31.19	−15.26	−5.17	3.85	3.58	−2.67	2.36	−2.32	2.31	−1.92	−1.74	−0.61	0.53	−0.51	−0.38	−0.14	0.12

4.4. Predicted LULC map for 2025

In general, the LULC prediction for 2025 carried forward the pattern of 1985–2005 i.e., decrease in forest classes and increase in cropland and built-up classes were observed for both the basins (Fig. 4).

The deciduous broad leaved forest, mixed forest, mangrove would show predicted area of 68339 km^2, 10575 km^2, and 170 km^2 respectively in MRB; whereas the evergreen broad leaved forest, deciduous broad leaved forest and mixed forest would show predicted area with 8636 km^2, 102501 km^2 and 60280 km^2 respectively in BRB (Fig. 4; Table 1). The total area for built-up and cropland was predicted to be 4550 km^2 and 149700 km^2 respectively in MRB; and 3886 km^2 and 51883 km^2 respectively in BRB (Fig. 4; Table 1).

In MRB, the maximum decrease in deciduous broad leaved forest is predicted with 1043 km^2 followed by 333 km^2 in mixed forest during 2005–2025; whereas the maximum increase could be observed in cropland with 943 km^2 followed by built-up with 572 km^2 (Fig. 4a; Table 1). Increase in water body, plantation and

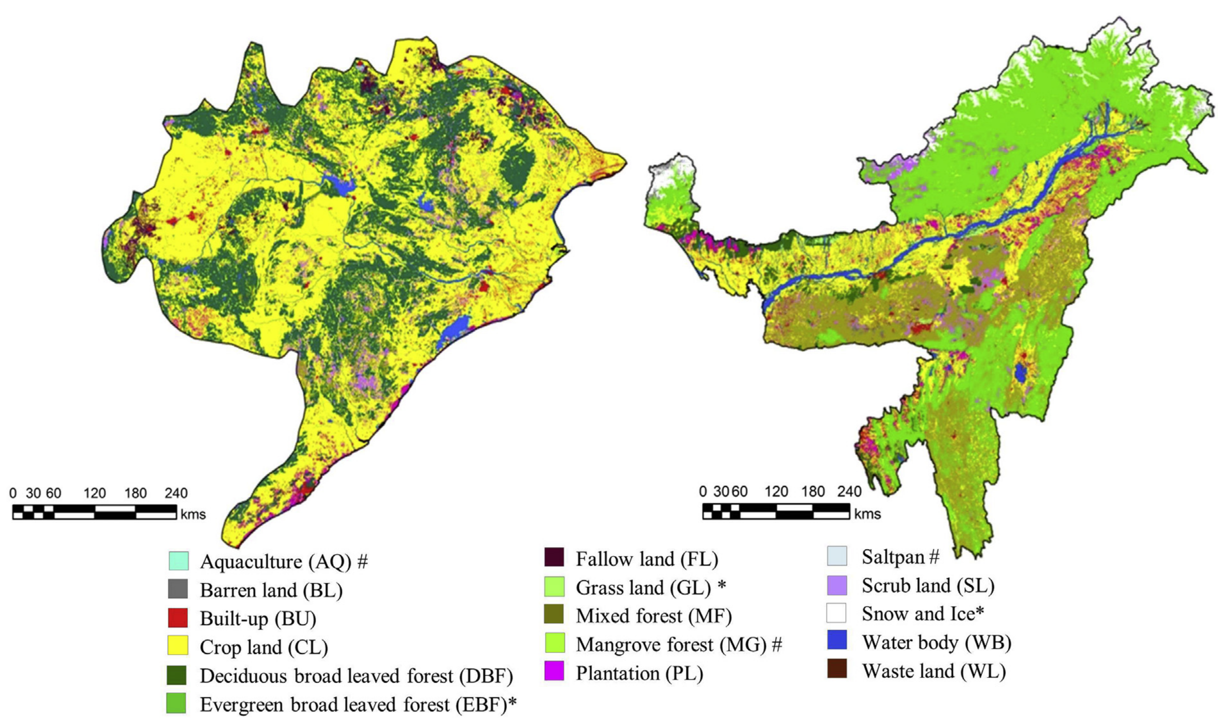

Fig. 4. Predicted LULC maps of (a) MRB and (b) BRB for the year 2025.

wasteland areas has been predicted showing a gain of 337 km^2, 96 km^2 and 27 km^2 respectively (Fig. 4a; Table 1). In BRB, the maximum loss has been predicted for mixed forest with 1532 km^2 area followed by decrease of 1286 km^2 for the evergreen broad leaved forest and 438 km^2 for deciduous broad leaved forest (Fig. 4b; Table 1). Grassland, plantation, snow and ice have been predicted with a loss of nearly 114 km^2, 73 km^2 and 8 km^2 area respectively (Fig. 4b); whereas an increase of 2641 km^2 and 239 km^2 has been predicted for cropland and built-up areas respectively (Table 1). Water body, shrub land and wasteland could show a gain of 341 km^2, 158 km^2 and 27 km^2 areas respectively as per the model prediction (Fig. 4b; Table 1).

We further analysed the logistic relationship between the major LULC changes and changed drivers for the year 1985–1995. The major conversions of forest classes, water body, grass and shrub land to cropland were observed for the study period in BRB. Conversions of cropland to water body and water body to grassland were also prominent in the basin. In MRB, conversions from deciduous broad leaved forest, mixed forest, shrub land, fallow land and water body to cropland were prominent. In addition, deciduous broad leaved forest, shrub land, cropland to water body; cropland to built-up; mixed forest to shrub land and shrub land to wasteland were observed to have conversions of >100 km^2 magnitude. Positive β values indicate the positive relationship between the changes in driver with the change in LULC, i.e. an increase in the value of a driver would cause the increase in the corresponding LULC change and *vice versa*.

In general, the distance drivers and population drivers played dominant role in conversion of forest classes to cropland having a higher β coefficients in both the basins (Table 4). In BRB, positive correlation was observed for evergreen broad leaved forest to cropland conversion with distance to forest driver and total population showing β values of 1575 and 944.54 respectively (Table 4). Deciduous broad leaved forest to cropland conversion showed a positive relation with population density, total and working population with a β values of 224, 162 and 128 respectively (Table 4). Mixed forest to cropland conversion positively influenced by distance to forest with a β value of 58 and negatively influenced by literacy rate (β, −49) respectively.

In MRB, cropland to built-up conversion was influenced negatively by distance to built-up and positively by literacy rate and population density showing β values of nearly −67, 18 and 8 respectively (Table 4). Major conversion to cropland was observed from the fallow land, shrub land and water body classes, where establishment and population density had a negative influence on conversion from fallow land to cropland showing a β values of −101 and −80 and positive influence of literacy rate with a β value of 18.5 respectively. Conversion of mixed forest to shrub land was influenced negatively by temperature and road length with a β value of −89 and −6.5 respectively (Table 4).

5. Discussion

5.1. LULC mapping and change detection

The output maps and results of our first objective of LULC status in MRB and BRB during 1985–2005 at decadal interval impart meaningful knowledge by integrating ecological information into image interpretation exercises (Behera et al., 2005). As there was no control on the past satellite data w.r.t. the spatial and spectral resolution, the digital classification would be erroneous. The on-screen visual interpretation technique utilised for LULC classification demonstrated control on each polygon boundary in comparison to other algorithm based classification techniques (Roy et al., 2015a; Behera et al., 2014). We observed higher confidence due to available ground truth information showing >90% of accuracy and the mapped data might be served as a validation input in many modelling exercises in future. Although visual interpretation is time consuming, the efficacy of the method by providing more control in classified polygons enhances the accuracy (Roy et al., 2015b). In addition to the spectral response of the images the analyst knows several aspects of study area based on the reconnaissance survey which emphasizes to prior knowledge of an interpreter and helps to define classes to be more representative of the real terrain conditions. Moreover, the problem of mixed pixels was addressed by visual interpretation especially for the mixed forests and built up areas that are a heterogeneous mixture of types including buildings, grass, roads, water etc. (Jensen and Im, 2007). Visual interpretation was shown to have more quality control over digital classification for analysing medium resolution satellite data. Ghorbani and Pakravan (2013) observed more precise results of visual interpretation compared to digital classification. The

Table 4
Logistic regression results of the LULC change with the change in driver for the period 1985 to 1995 ($p < 0.005$).

BRB			MRB		
Conversion Type	Drivers	Coefficient (β)	Conversion Type	Drivers	Coefficient (β)
GL-CL	DW	−5.80	FL-CL	LR	18.53
	EB	−6.93		PD	−80.55
	RF	5.73		DW	−4.60
EBF-CL	EB	31.19	SL-CL	PD	3.26
	DF	1575.00		RL	0.80
	TP	944.54	WB-CL	DW	239.17
	MT	44.36		LR	7.32
	WP	17.97		PD	8.25
DBF-CL	PD	223.80	SL-WB	DW	−13.43
	RF	−62.06	DBF-WB	DF	1167.00
	TP	161.81		DW	−8.52
	WP	127.64	CL-WB	DW	−26.40
MF-CL	DF	58.18	CL-BU	LR	18.65
	LR	−48.76		PD	8.21
	PD	3.65		DB	−67.91
SL-CL	DF	131.25	MF-SL	DW	−38.27
	TP	143.75		MF	32.25
WB-CL	DW	336.95		RL	−6.50
WB-GL	DW	399.17		MT	−89.33
CL-WB	DW	−336.26	SL-WL	DF	69.07

misclassification was observed in the boundary region of few classes shows similar reflectance patterns and closely associated as various forest classes as deciduous broad leaved forest, mixed forest, and evergreen broad leaved forest; agriculture land with grass and scrubland. Additionally, the confusion was also observed in the classes having very small patches *i.e*., barren land, built-up, saltpan etc which are harder to discriminate in a moderate resolution satellite data (i.e., Landsat MSS). Despite being time-consuming and less repetitive in nature, visual interpretation allows a user to delineate realistic objects by interpreting complex spatial patterns using interpretation keys.

The biogeography of both the basins vary drastically as BRB accommodates hilly terrain (maximum height of >8000 m a.m.s.l) with snow and rain fed characteristics, while, MRB is comparatively plain with <2000 m height a.m.s.l. We observed an overall increase in cropland and decrease in forests in both the river basins in both decades (Fig. 2). The decrease in forests *i.e*., deciduous broad leaved forest, evergreen broad leaved forest and mixed forest was at the expense of increase in cropland, built-up and water body. The conversion of dense forest to cropland is prominent in both the basins indicating increasing population dependency. Both the basins showed an increase in the population density for the studied decade which significantly affected the deforestation rate.

Due to the reservoir constructions, intensive agricultural practices took place leading to loss of forests and barren lands in MRB basin. It is evident from change matrix that major decline in forest classes has taken place due to high conversion to cropland and built-up as a result of anthropogenic pressure (Table 2). Large patches of deciduous broad leaved forests were deforested during construction of Hasedo reservoir and other reservoirs like Chandil, Thenga, Harabhangi, Badanallah, Soundur and Indravati dam etc; and expansion in area of Ganrel, Bhaskel, Dudhawa, Sundar dam and reservoirs. Madduvalasa and Baghua reservoir were constructed during 1995–2005 (India WRIS; http://india-wris.nrsc.gov.in/wrpinfo/index.php?title=Dams_in_Chhattisgarh for the list of construction of various reservoirs in Mahanadi). Similar pattern of high magnitude deforestation rate for agriculture land expansions were also reported in past studies (Mishra, 2008; Reddy et al., 2009; Giri et al., 2008). Additionally, the development of coastal cropland and shrimp farming ponds are other cause for mangrove decline (DasGupta and Shaw, 2013). Increase in built-up area could be corroborated with the rise in industrial and manufacturing complexes in this region. The basin comprises of major urban centres namely Raipur, Durg and Cuttack and because of its rich mineral reserves and adequate power resources it has an industrial suitability thereby leading to urban expansion. Rural to urban transformation, migration and economic development in these areas in the past decade were also significant (Kumar et al., 2014). Recently the decision of expansion of additional 580 km^2 around the Bhubaneswar city, a major city within MRB, and inclusion of 367 revenue villages by state govt. took momentous measures in conversion of regional LULC scenarios and would impact the future built-up scenarios as well (3rd Jan., 2011, Telegraph). Built-up expansions would be near to existing built-up, distant to forest, low elevated, flat terrain, having higher soil depth, populated areas with higher road lengths. Projected scenario of 2025 with the last decade LULCC trend predicted even higher magnitude of built-up expansion by means of both cropland and plantation loss, followed by deforestation. Most of the built-up expansions were predicted in and around the exiting built-up areas highlighting the same trends observed in the past two decades.

In contrast to MRB, the rate of deforestation was two times higher in BRB, where big patches of evergreen broad leaved forest and deciduous broad leaved forest at lower slope in the basins were cleared for agricultural activities, as evident from the satellite images (Fig. S5). The decrease of forest area in BRB could be attributed to increased biotic pressure, shifting cultivation and shrinkage of shifting cultivation cycle (FSI, 2011; Lele and Joshi, 2009, Srivastava et al., 2002; Kushwaha and Hazarika, 2004). Shifting cultivation, also known as 'jhum' or slash and burn practice, in north east India is one of the most detrimental practice leads to forest fragmentation and continuing to expand yearly. This practice is more intense in Meghalaya, Nagaland and hilly regions of Assam. Nearly 0.45 million families annually cultivate 10,000 km^2 forests in BRB. BRB has undergone several internal and external migrations of vast population in the form of labourers, refugees from the neighbouring countries i.e. Bangladesh, Srilanka, Nepal, Tibet. This resulted in huge forest area encroachment for livelihood dependencies. As per Nath and Mwchahary (2012), the population of Kokrajhar district of Assam was tripled with five times higher population alone in the forest area during 1961–2001. During British period various tea gardens were encouraged at the expense of deforestation (Khataniar, 2014). In addition, the opening of commercialized timber mills in the region during 20th century led to the degradation of upper Assam forests by > 1763 km^2 as per the Central Forestry Commission. Alone in Assam the districts of North Cachar Hills, Karbi Anglong, Karimganj and Hailakandi showed a loss due to shifting cultivation while Sonitpur, Darrang and Karbi Anglong showed an illicit felling to be the most causal factor of deforestation (Khataniar, 2014). The other drivers of forest loss in the basin include spread of smallholder agriculturalists, timber consumption with illegal felling and logging in forest areas (Saikia, 2014). According to State Forest Report (FSI, 1997), BRB lost 1734 km^2 forest covers during 1989–1995.

Following the past trend, the model also predicted increase of cropland and urban area at the cost of forest cover loss in both the basins. LULC change and extensive agricultural activities leads to the deterioration of the quality of natural water. MRB is dominated agriculturally and has undergone establishments of industries, thus subjected to huge quantities of fertilizers, sewage loads, and effluents from industries etc. which get leached or brought into the river water leading to nutrient enrichment and so the growth of microorganisms and as a consequence depletion of oxygen was observed (Dixit et al., 2013). A study by Ghosh et al. (2013) in Dhalai basin, Tripura observed the more susceptibility of soil loss by water erosion in agricultural land and degraded forest cover than dense forest. The impact of LULC change on BRB can be expressed in terms of flooding, changes in hydrology and soil nutrient degradation. In contrast, MRB can express the impact of LULC change in terms of soil degradation by increased acidity, toxicity; in addition loss of water quality by addition of fertilizers can be more prominent in MRB. Thus, a study on LULC change and its future prediction at basin scale can offer much needed inputs for policy decision making and proper resource management.

5.2. Analysis of drivers

The high accuracy of predicted map of 2005 for both the basins (overall accuracy >97%) showed the reliability of the model and significant impact of the drivers on LULC change (Table S4). This provided confidence in generating the LULC scenario for the year 2025. The small mismatch could be attributed to the addition of more pixels to the classes having less area *i.e*., aquaculture, barren land and wasteland. It is obvious to have negative relationship of forest class with 'distance to forest drivers', since the occurrence probability of forest decreases with increased distance. Similarly, expansion of built-up area is less expected with increased distance to built-up since the patch contiguity and patch density plays a

major role in urbanization *i.e.*, higher the patch density or patch area, higher the degree of built-up expansion in future.

In MRB, total population showed a negative relation with mangrove, which could be attributed to its coastal presence, where the population density is minimal. Cropland class had a negative influence of slope as cropping is discouraged on higher slopes due to higher erosion risks. It has been observed that the agricultural activities are associated with the rural population and distance from the natural forest; thus, the decreased distance from forest limits the presence of cropland. The positive relation between sex ratio and mixed forest deforestation could be attributed to higher deforestation with higher women population as they primarily collets fuelwood and fodder from forests (Agarwal, 1991; Nagbrahmam, and Sambrani, 1983). In BRB, positive relation of grassland with elevation was observed due to the presence of temperate grasslands dominated by *Themeda-Arundinella* type along with the Riverine grasslands at higher elevations. Snow and ice had a positive relation with elevation since lower temperature is experienced at higher elevations.

5.3. Driver analysis through LULC change

The population drivers were more prominent in BRB to influence conversion to cropland. In contrast, distance driver impact was prominent in MRB for conversion to cropland. The positive influence of establishment, total population can be explained in the fact that within the studied time period there has been an increase in population of BRB, thus it is obvious to have dependency of a large population on agriculture for livelihood. In addition, the slash and burn technique practiced by the tribes in BRB led to the conversion of forests and shrub land to cropland with increased population. The distance to forest increase leads to the low forest density and more fragmented area in the transition zone of forest thus we get positive relation with the driver.

Higher positive β value of distance to water body against conversions of water body to cropland and grassland and *vice versa* explains the river dynamics of the basin. In BRB, the accumulation of eroded soil in the plains of northeast India leads to the continuous changes in the river course (Table 3b). Thus, the cropland and grass land along the river side with less distance to water body are more prone to convert to water body and *vice versa*.

In MRB, positive influence of population density for the conversion of cropland to built-up could be attributed to the increasing demand of household to support the escalating population. The negative relation of cropland to built-up change with distance to built-up could be explained by the fact that patch contiguity and patch area plays a major role in urbanization *i.e.*, higher the patch area, higher the degree of built-up expansion in future. Increasing food demand and suitable site conditions due to availability of sufficient water led to the conversion of fallow and shrub land to cropland. The negative influence of 'distance to water body' driver for the conversion of different LULC classes to water body could be attributed to the construction and expansion of dams and reservoirs. The Dyna-CLUE model has been used successfully for transforming the drivers influence on future land conversion in these two river basins, thus imitating the trends in a realistic way. Continuous deforestation may impose significant hydrological and ecological changes by altering rainfall patterns. Prasad (2016) observed a 100–200 mm reduction in summer monsoon and 1–2 mm reduction of per day rainfall in Ganga River basin and North east India due to conversion of forest to tea crop. Das et al. (2017) have observed a significant decrease in evapotranspiration with increased runoff and baseflow due to conversion of forested region to cropland and built up in the MRB.

6. Conclusions

The study has analysed the decadal (1985-1995-2005) LULC changes in two major River basins of India using satellite imagery. Remarkably, higher agricultural expansion, deforestation and urbanization due to developmental activities have caused alteration in LULC status. The influence of drivers is prominent where proximity holds the keys. LULC change is driven by environmental and socio-economic drivers and the pattern is carried forward to predict the LULC map of 2025. The variability in drivers or the predictor variables works as a major factor for future LULC change estimation because of their spatial organisation.

The increase in water bodies in two River basins have been attributed to different LULC changes such as in MRB; it is due to creation of many reservoirs and aquaculture farms, whereas in BRB it is mainly due to melting of snow and ice. In both the basins, the built-up areas have increased and would continue to increase at the expense of any other LULC classes, except snow and ice in BRB owing to unsuitable conditions. Plantation activities have been carried out mainly in waste land, fallow land and barren land classes in both the river basins, whereas in BRB, many crop land areas have been diverted to plantation of cash crop such as tea and rubber. The conversion of scrub land has different routes *i.e.*, in MRB the decrease in scrub land classes is mostly due to conversion to agricultural classes, whereas in BRB, scrub land acts as an intermediate class through conversion of forest to non-forest land. Similarly in MRB, most of waste and fallow lands were converted to agriculture or built-up classes; wherein, in BRB, most of the deforested lands remain for long as waste/fallow land before getting converted to other LULC classes. The major driver of LULC changes in BRB is found to be population presence, whereas in MRB it is the distance or proximity to the anthropogenic sources.

Analysing these LULC change and their impacts at River-basin level is an important step forward for a developing country in the context of today's increasing focus on integrated water resources management (IWRM) in River basins. However, to understand such impacts of LULC change, accurate and efficient techniques are necessary to provide the information on spatio-temporal changes, their rates at which they occur and the drivers that drive these changes (Lambin, 1997). Therefore, LULC change map is essential for predictive analysis study providing useful information for decision-making. The LULC change models reflect the ecological balance response to changes and thus are useful for studying the dynamics of land-use planning. However, the future work might include a comparison using more rigorous statistics in predicting LULC to emphasize the driver relationship along with pattern of change. Since we are already in 2015, there is a need of mapping the LULC scenario to judge the change pattern in last decade.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvman.2017.10.015.

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